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RESEARCH PAPER

Application of Genetic Algorithm in Dynamic Route Guidance System

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Abstract: By applying random A* algorithm, this paper clears out the biggest obstruction between the genetic algorithm and dynamic route guidance of how to get the initial generation of genetic algorithm. The developed models and algorithms are implemented with Guangzhou's electronic map and their computational performance is analyzed experimentally. The results indicate that dynamic route guidance A* algorithm is suitable for route guidance problem in FIFO dynamic network, dynamic route guidance Q-learning algorithm is suited for route guidance problem in steady non-FIFO dynamic network, and dynamic route guidance genetic algorithm is suitable for route guidance problem in vertiginous non-FIFO dynamic network.

Key Words: random A* algorithm; electronic maps; DPGS (dynamic path guidance system); shortest path; genetic algorithm

Introduction

With the development of economy, transportation is growing at a rapid speed. Newly built roads and other transportation establishment such as one-way street, no entry street, and no turn street are more and more widely adopted. To drivers, on the one hand, these transportation facilities have provided them with more route selections; on the other hand they have also increased the trip's complexity. According to this condition, drivers need a trip service to avoid the rush and go against disciplines on the trip. Traffic directors also hope that traffic flows can be distributed rationally on the entire road networks to the greatest degree. Dynamic path guidance system is an effective approach to resolve these problems. The computation of the shortest paths in dynamic networks is at the heart of DPGS. For instance, in the context of intelligent transportation system (ITS) applications, the computation of the shortest paths is a fundamental component in route guidance systems and in the development of solution algorithms for large-scale dynamic network flow models. DPGS is a key part of ITS, which is based on electronic, computer, network, and communications modern techniques. By real-time traffic information, DPGS has found out a shortest path from an origin node to a destination node for drivers. It mainly depends on the effectiveness of shortest paths algorithms and integrality of electronic maps. Dynamic shortest path problem was first proposed by Ziliaskopulos. One of the celebrated results for this problem is: when the FIFO (First-in-first-out) property is satisfied, any static shortest path algorithm can be generalized to solve the dynamic shortest path problems for a given departure time with the complexity as the static shortest path problems. Kaufman and Smith were first to suggest this generalization heuristically. But there is no appropriate algorithm for the shortest path problems in non-FIFO dynamic network[1−5].

The origin of Genetic algorithm is attributed to Holland's work on cellular automata. There has been significant interest in genetic algorithm over the last two decades. The range of applications of genetic algorithm includes such diverse areas as: job shop scheduling, training neural networks, image feature extraction, and image feature identification. Gen shows that genetic algorithm can solve the shortest path problem on a simple undirected graph with static weights. The purpose of the exercise was not to compete with conventional algorithm, but to show an encoding scheme that might be

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extendable to more difficult problems for which no-known algorithm exists. The present study uses a different and more intuitive encoding scheme to solve the shortest path problem in non-FIFO dynamic networks. Considering genetic algorithm's properties, we propose the application of genetic algorithm to shortest paths problems in non-FIFO dynamic networks a problem where other algorithms are completely intractable[6−8]. The proposed approach is generally enough to allow for many practical applications.

1 Dynamic route guidance model and algorithm notation

Let $G=(N,A,S,D,K,MV)$ be a directed dynamic network based on an electronic map where $N=\{1,\cdots,n\}$ is the set of nodes, and $A=\{1,\cdots,m\}$ is the set of directed links. We denote $S=\{s_{ij}\mid(i,j)\in A\}$ by the set of link distance, $D=\{d_{ij}(t)\mid(i,j)\in A\}$ by the set of time-dependent link travel times. Functions $d_{ij}(t)$ have integer-valued domain and range. A function $d_{ij}(t)$ is then a discrete and time-dependent function which is assumed to take a static value after a finite number of intervals *M*. $T=\{0,\cdots,M-1\}$ is, hence, the set of departure time intervals for which link travel times are time-dependent. We denote $K=\{k_{ij}\mid i,j\in N\}$ by the set of linear distance between random two nodes, *MV* by the maximum vehicle speed in this network. Because $G=(N,A,S,D,K,MV)$ is based on real transportation network, the following two formulas must be satisfied:

$$(s_{i\,i_1}+s_{i_1i_3}+\cdots+s_{i_lj})\geq k_{ij} \qquad \forall(i\ ,i_1),(i_1,i_2),\cdots,(i_l.j)\in A \tag{1}$$

$$(s_{ij}/MV)\leq d_{ij}(t) \qquad t\in[0,\ M-1] \tag{2}$$

Equation (1) indicates that the linear distance between two nodes is less than any route between the two nodes; Eq. (2) indicates that s_{ij}/MV is the lower bound of link travel time.

The following are symbols used in describing random A* algorithm:

O: origin node;

P: destination node;

$L_i(t)$: minimum travel cost from node *O* to node *l*, departing the origin node *O* at time *t*;

$\hat{e}_{ij}(t)$: minimum travel cost from node *i* to node *j* at time *t*;

$\hat{e}_{ij}$: lower bound on minimum travel cost from node *i* to node *j* at time *t*;

$F_i(t)$: minimum travel cost among all paths from origin node *O* to destination node *P* constrained to go through node *i*, departing the origin node *O* at time *t*;

$\hat{L}_i(t)$: upper bound on minimum travel cost from node *O* to node *i*, departing the origin node *O* at time *t*;

$\hat{F}_i(t)$: estimate of $F_i(t)$, $\hat{F}_i(t)=\hat{L}_i(t)+\hat{e}_{ip}(t+\hat{L}_i(t))$;

$B(i)$: set of nodes having an outgoing link to node *i*;

C: set of nodes that have been reached and that are candidates for the selection of the next node;

S: set of nodes that have been selected, and that are not in set *C*.

2 Genetic algorithm description

Ever since the genetic algorithm was introduced by Holland to tackle combinatorial problems, it has emerged as one of the most efficient stochastic solution search procedures for solving various network design problems.

In order to solve the above model of stochastic shortest path problem, we employ genetic algorithm to find the paths. The representation structure, initialization, and genetic operators are as follows:

2.1 Genetic representation

Now, we use an integer vector $P=(v_1,v_2,\cdots,v_k)$ as a chromosome to represent a path of *G* from the origin node *O* to the destination node *P*. Because different paths include different nodes and arcs, the dimension of chromosome is not fixed. If $(v_1,v_2,\cdots,v_k)$ represent a path from the origin node *O* to the destination node *P*, then we have $(0,v_1)\in A$ $(v_1,v_2)\in A,\cdots,(v_{k-1},v_k)\in A$. So we have the definition of Eq. (3) for all $(i,j)\in A$.

$$x_{ij}=\begin{cases}1, & i=o,j=v_1\\ 1, & \exists l,i=v_l,j=v_{l+1}\\ 1 & i=v_k,j=p\\ 0 & otherwise,\end{cases} \tag{3}$$

It is also easy to verify that $\{x_{is}\mid(i,j)\in A\}$ obtained by this way is a path from the origin node *O* to the destination node *P*. Conversely, let $\{x_{is}\mid(i,j)\in A\}$ be a path from the origin node *O* to the destination node *P*. We may obtain a chromosome by the following procedure.

2.2 Chromosome initialization

In order to initialize a feasible chromosome, we propose random A* algorithm to make chromosomes. The following is a description of the random A* algorithm.

Step 1: initialization.

Set $i=0$, $\hat{L}_i(t)=0$, $\hat{F}_i(t)=\hat{e}_{ip}$; $\hat{L}_j(t)=\infty$, $\hat{F}_j(t)=\infty$, $\forall j\neq i$; $C=\{i\}$; $S=\phi$;

Step 2: node selection.

A node $i\in C$ is selected with the probability $\hat{F}_j(t)/\sum_{l\in C}\hat{F}_l(t)$; $S=S\bigcup\{i\},C=C\setminus\{i\}$;

Step 3: stopping rule.

If *i*=*p*, then stop. Otherwise, continue.

Step 4: update $\hat{F}_i(t)$ and distance labels $\hat{L}_i(t)$.

For each $j\in A(i)$: If $\hat{L}_i(t)+d_{ij}(t+\hat{L}_i(t))<\hat{L}_j(t)$, then $\hat{L}_j(t)=\hat{L}_i(t)+d_{ij}(t+\hat{L}_i(t))$; $\hat{F}_j(t)=\hat{L}_i(t)+d_{ij}(t+\hat{L}_i(t))+\hat{e}_{jp}$; if $j\notin C,C=C\bigcup\{j\}$, go back to Step 2.

For all $(i,j)\in A$, let $d_{ij}^{\min}=\min_{t=0,1,\cdots,M-1}\{d_{ij}(t)\}$. We construct a virtual static network with $d_{ij}^{\min}$ as the link travel times. An all-to-one static shortest path algorithm applied to the virtual network and destination node *P* leads to minimum travel time denoted by e_{ip} from every node i to P. e_{ip} is able to be computed by Dijkstra algorithm.

2.3 Chromosome crossover

Genetic operators mimic the process of heredity of genes to generate new offspring at each generation and play a very important role in genetic algorithm. In our algorithm, the crossover operator, mutation operator and selection are as follows:

Let $P_1 = (v_1, v_2, \cdots, v_k)$ and $P_2 = (v'_1, v'_2, \cdots, v'_{k'})$ be two chromosomes. We will do crossover operation on them as follows: if there are common nodes between them, then we randomly choose one $v_i = v'_{i'}$. The following chromosomes are produced:

$$v_1, v_2, \cdots, v_i, v'_{i'+1}, \cdots, v'_{k'}, v'_1, v'_2, \cdots, v'_i, v_{i+1}, \cdots, v_k$$

which are also feasible chromosomes representing path from node O to P. If there is no common node, then the following chromosomes are produced:

$$v_1, v_2, \cdots, v_{i'}, v''_1, \cdots v''_l, v'_{j'}, \cdots, v'_{k'}$$

which are also feasible chromosomes representing path from node O to P.

Let $e'_{v_{i'}v'_{j'}} = \min_{i=1,\cdots,k;j=1,\cdots,k'} e'_{v_i v'_j}$, and e'_{ij} denotes the minimum travel cost from node i to node j in dynamic network $G' = (N, A, D')$. e'_{ij} can be computed by Dijkstra algorithm. We denote $D' = \{d'_{ij} = [\sum_{t=0,1,\cdots M-1} d_{ij}(t)]/M\}$ by the set of link average travel times. The path ($v_{i'}, v''_1, \cdots v''_l, v'_{j'}$) from $v_{i'}$ to $v'_{j'}$ is made by a similar process of chromosome initialization in dynamic network G'.

2.4 Chromosome mutation

Let $P = (v_1, v_2, \cdots, v_k)$ be a chromosome, we can mutate it by the following way. Generate an integer from $\{1, 2, \cdots, k\}$ randomly, denoted by i. Then we make a path $(v'_{i+1}, \cdots, v'_{k'})$ from v_i to p by a similar process of chromosome initialization, and produce a new chromosome $(v_1, v_2, \cdots, v_i, v'_{i+1}, \cdots, v'_{k'})$.

The roulette wheel selection is adopted in our algorithm. We select a single chromosome each time for a new population until population size copies are finally obtained.

3 Computer implement and experimental evaluation

The adaptation of Genetic algorithm in shortest dynamic path problem discussed in the previous sections has been implemented for the purpose of computational testing of the validity of the adaptation of Genetic algorithm proposed in this paper in this section. The algorithm was implemented using C++ programming language and tested on a non-FIFO dynamic network based on Guangzhou City's electronic map containing 20000 nodes, 40000 links and 144 time intervals. We selected ten Origin-Destination (OD) pairs in the network to test the algorithm.

Table 1 depicts the parameters of genetic algorithm, and Table 2 depicts the experimental results. As Table 2 indicates, the average computation time is 7.2 s, and the average error is 15.5. Numerical results show that the adaptation of Genetic algorithm developed in this paper is effective.

Table 1 Parameters of genetic algorithm

Number of population	Number of generation	Crossover ratio	Mutation ratio
50	100	60	0.1

Table 2 Results of the network

OD	Average computation time (s)	Average errors
1	11.3	20.7
2	2.3	12.6
3	10.8	18.8
4	13.9	25.1
5	5.8	15.4
6	4.9	14.9
7	13.4	26.9
8	3.9	10.8
9	1.8	2.7
10	3.7	7.4

4 Conclusions

This paper has proposed a new algorithm for the shortest path problem in dynamic network that does not satisfy the FIFO property by using Genetic algorithm. The dynamic adaptation of the genetic algorithm is based on random A* algorithm proposed in this paper. The adapted algorithm has been implanted and their computational performance experimentally evaluated and tested. These experimental results demonstrate the utility Genetic algorithm on a very large scale dynamic optimization problem. The results also suggest that approaches to decentralized control using Genetic algorithm have considerable promise. Future research on the dynamic shortest path problem will investigate and further explore the parallel and decentralized Genetic algorithm architectures.

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